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Your presentation Taken note

Reconstruction of Dynamic Perfusion and Angiography Images from Sub-sampled Hadamard Time-encoded ASL Data using Deep Convolutional Neural Networks

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Purpose/Introduction

Arterial spin labeling (ASL) is a non-invasive technique for acquiring quantitative measures of cerebral blood flow (CBF)[1]. Hadamard time-encoded(te) pCASL allows time-efficient acquisition of dynamic ASL-data and when done with and without flow-crushing, 4D MRA and arterial input function measurements can be obtained[2]. While improving quantification, this approach is also a factor two slower. In this study, we propose an end-to-end 3D convolutional neural network (CNN) in order to accelerate CBF quantification from sparse sampling (50%) of te-pCASL with and without flow crushers. For training and evaluation of the CNN, we propose a framework to simulate the te-PCASL signal.

Subjects and Methods

Fig. 1a shows the proposed framework for generating the training and validation data. The ASL signal is simulated by a tracer kinetic model of te-pCASL. This model is a function of arterial arrival time, tissue arrival time and blood flow, which were extracted from in vivo data and registered to BrainWeb[3] scans. This study contains 1676 simulated subjects, each including crushed and non-crushed input data at 8 timepoints, and angiographic and perfusion output data at 7 timepoints. The proposed CNN, Fig. 1b, leverages design elements from DenseNet4 with loop connectivity patterns in a typical U-shape (~400K parameters). We leverage a Huber loss function for training the network, with weights based on the gradient magnitudes from Fig. 2a. In order to manage memory usage, we utilize patch-based training. The simulated dataset was divided into 1174 subjects for training, 167 for validation, and 335 for testing. For augmenting the training data, noise, flipping and ±13° rotation have been applied randomly. The network was trained for 30k iterations.

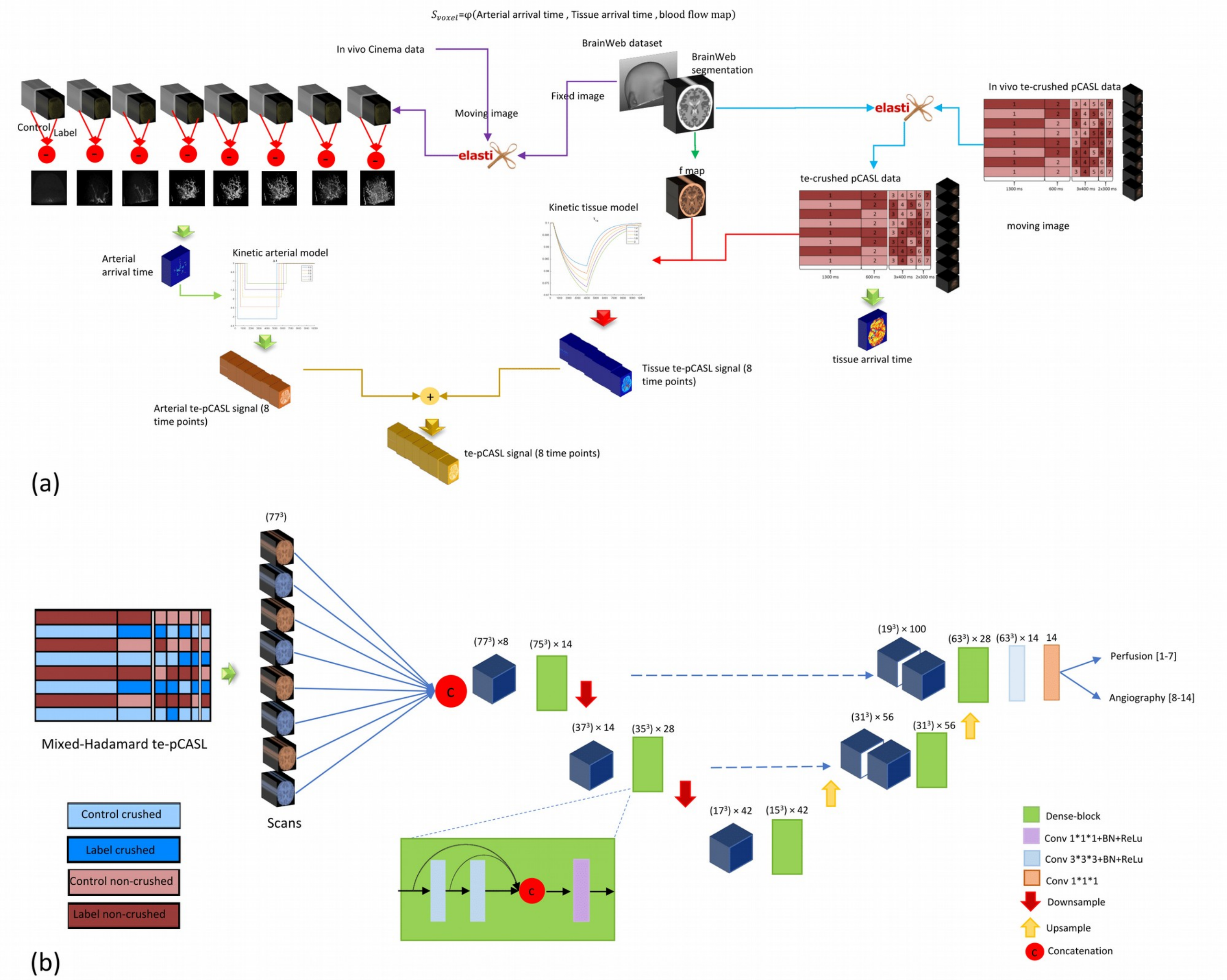

Fig. 1- a) Simulated data generator framework; b) the proposed CNN

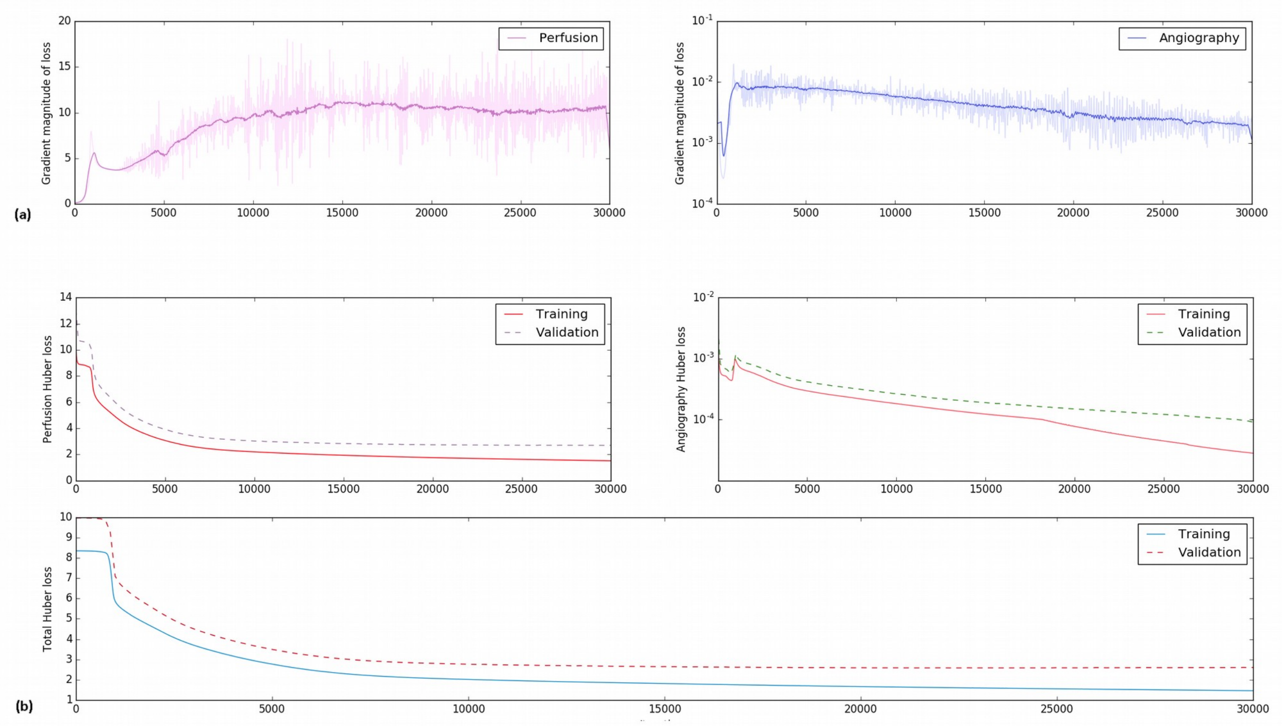

Fig. 2- a) Gradient magnitude b) loss functions for angiography/perfusion during training

Results

Fig. 2b, shows the network's training loss for the perfusion and angiography separately and their combination. The average MSE for the perfusion and the angiography is 5.30±0.22 and 5.02±0.17. Fig. 3 shows the outputs of the network for some slices of perfusion/angiography at different timepoints. Due to the averaging property in the Huber loss function, the results suffer from over-smoothing. It takes an average of 0.12±0.18s to reconstruct all perfusion and angiography scans from the sparsely-sampled crushed/non-crushed data (size 101^3).

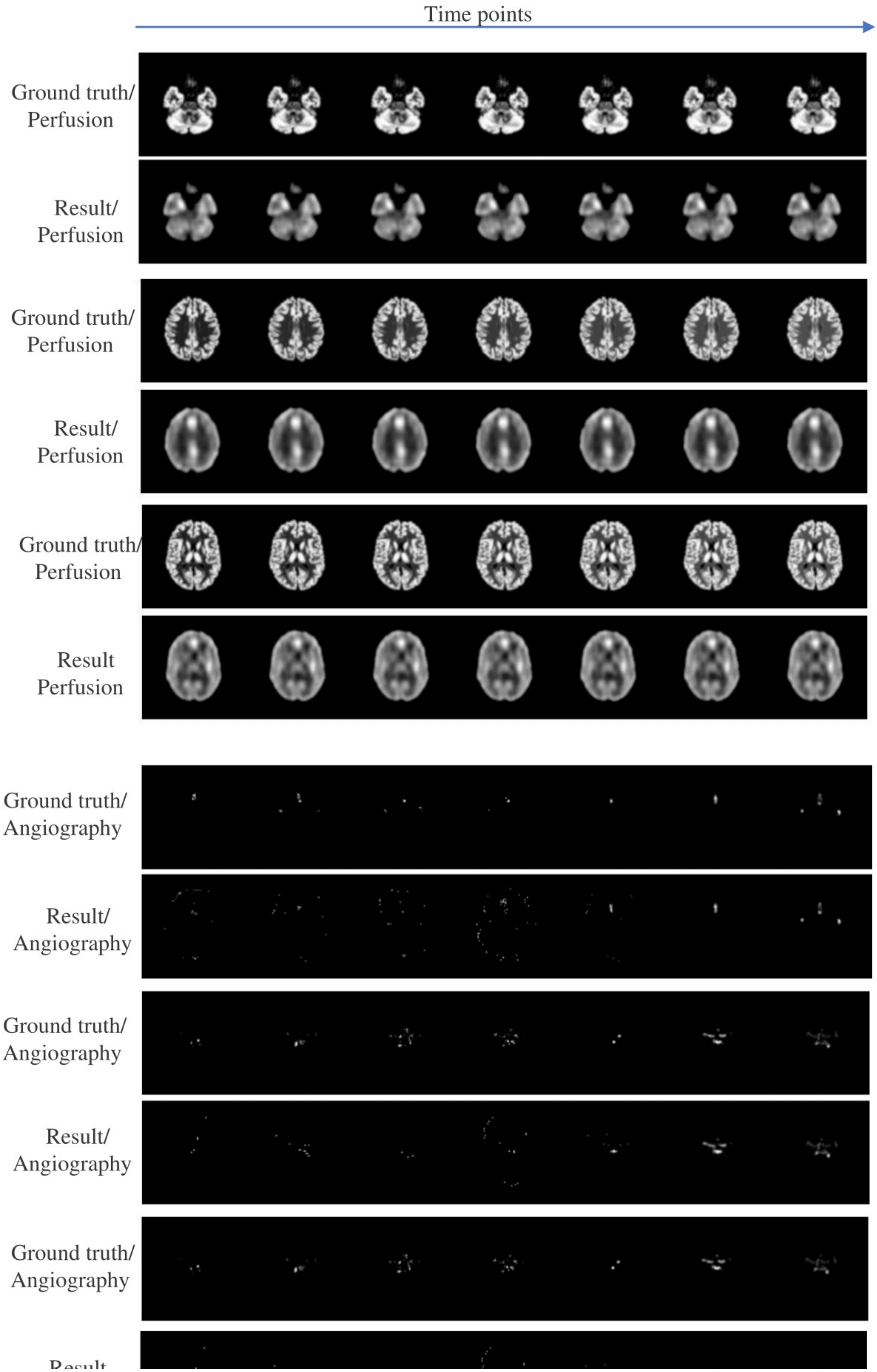
Time points
Ground truth/ Perfusion
Result/ Perfusion
Ground truth/ Perfusion
Result/ Perfusion
Ground truth/ Perfusion
Result Perfusion
Ground truth/ Angiography
Result/ Angiography
Ground truth/ Angiography
Result/ Angiography
Ground truth/ Angiography

Fig. 3- Example results

Discussion/Conclusion

This study demonstrates that CNNs are promising to reconstruct angiographic and perfusion images from sparsely sampled Hadamard ASL-data. A next step is the use of perceptual losses to improve sharpness of the results, as well as validation on in vivo data.

References

1. Teeuwisse et al. MRM, 1712-1722, 2014
2. Petersen et al. MRM, 219-232, 2006
3. Cocosco et al. NeuroImage. 1997
4. Huang et al. IEEE CVPR, 4700, 2017

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